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Crop Identification and Analysis Based on Spatial Features by Using Geospatial Technology

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1. Introduction

The increasing demand for environmentally sustainable intensification of agriculture to support an increasing global population has propelled the evolution of conventional farming into data-intensive, technology-enabled systems [1]. Precision agriculture (PA), an emerging paradigm that integrates spatial and temporal variability into agricultural practices, is a revolutionary model in modern agronomy. Precision agriculture is founded on systematic acquisition, processing, and interpretation of high-resolution data to optimize input use efficiency, increase productivity, and reduce environmental footprints [2]. Precision agriculture's imperative necessity is elucidated through its capacity to reverse issues of climate variability, soil heterogeneity, pest and disease management, and inefficient use of resources [3].

One of the deepest applications of precision agriculture lies in monitoring crop health, in which physiological stressors (e.g., nutrient deficiencies, water stress, pest infestation) are identified at an early stage, and hence interventions are undertaken on time [2][4]. The benefits of this preemptive action include better yield stability, less economic loss, enhanced efficiency in using inputs (e.g., fertilizers, irrigation), and enhanced profitability for the entire farm. Moreover, regular crop monitoring helps interpret inter-field variation and aids evidence-based decision-making at both micro and macro levels [1][5].

Geospatial technology is at the heart of precision agriculture, a technological field covering Geographic Information Systems (GIS), Global Navigation Satellite Systems (GNSS), and Earth Observation (EO) infrastructure like remote sensing [6]. They facilitate geographically explicit monitoring, mapping, and modeling of agro-ecological events. The combination of geospatial analytics and precision agriculture has transformed field-level decision-making systems through real-time monitoring, trend analysis of past patterns, and predictive modeling of crop performance in varied agro-climatic zones [7].

Satellite remote sensing (e.g., Sentinel-2, Landsat-8/9, LISS-IV), proximal sensors and unmanned aerial systems (UAVs) play critical role in crop health diagnostics. It allows derivation of biophysical markers including the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), chlorophyll content, and water stress indices [8]. These markers provide a non-destructive, scalable, and temporally homogeneous means for evaluating crop vigor, disease incidence, and phenological changes. Integrating these data with GIS-based spatial analysis enables the creation of high-resolution maps of crop health, anomaly detection, and hotspot intervention zones [9][10].

The relevance of geospatial technology in crop health analysis is several. It first facilitates precision targeting of agricultural inputs and thus reduces wastage and minimizes environmental degradation [11]. It secondly allows temporal monitoring, which is necessary for comprehending crop growth trends and predicting potential stress occurrences [12]. Third, geospatial data are used

as vital inputs for machine learning algorithms and decision support systems, improving the accuracy and detail of crop yield predictions and risk assessments [13].

Satellite imaging, especially by means of multispectral and hyperspectral sensors, has value in crop analysis because it measures reflectance values across specific spectral bands representing different physiological and biochemical characteristics of vegetation [14]. Bands in the visible spectrum (for example, red, green, and blue) can speak to general plant vigor, quantifying relative chlorophyll concentration, but the red-edge and near-infrared (NIR) bands are extremely sensitive to canopy structure, leaf area index (LAI), and biomass. Shortwave infrared (SWIR) bands inform us regarding plant water status, lignin, and content of cellulose and hence useful in detecting drought stress and senescence [15]. By examining these spectral bands in isolation and via vegetation indices (e.g., NDVI, EVI, NDWI), scientists can track plant health, phenological phases, nutrition levels, and stress diseases at high spatial and temporal resolution. The potential to derive such information from satellite images allows for non-invasive, wide-area, and low-cost crop diagnosis vital to precision agriculture and sustainable farm management [15][16].

2. Literature Review

Remote sensing crop classification is a fast-changing domain that harnesses cutting-edge technologies to enhance farm monitoring and management. High-resolution images are made available through remote sensing, which are analyzed using machine learning algorithms to accurately classify crops. Such a fusion is essential to enhance resource utilization, track crop well-being, and maintain food security. Employment of different machine learning algorithms like Random Forest, Support Vector Machines, and deep learning methods such as CNNs has proved promising to improve the classification accuracy. The following subtopics explore detailed methodologies and improvements in this field.

One of the study of remote sensing and machine learning application to classify crops based on Sentinel-2 data and NDVI-derived spectral characteristics. These techniques were utilized to classify crops including Cotton, Paddy, and Chickpeas, i.e., Random Forest, SAM, MLC, K-means, and ISODATA. Out of these, the Random Forest method emerged as the best, yielding an accuracy of 87.71% with kappa value 0.86, underlining its suitability for agricultural monitoring [17]. In another study for Crop classification based on remote sensing and machine learning utilizes multispectral, hyperspectral, and SAR satellite data with sophisticated algorithms such as CNNs, ANNs, and ensemble techniques to enhance classification accuracy. The method addresses issues like inadequate ground truth data, cloud cover, and seasonal variation, and research continues to integrate multi-sensor data and increase resolution for real-time observation and precision agriculture [18].

Another research demonstrates the application of Sentinel-2A's NDRE index and machine learning classifiers, including SVM, Random Forest, Decision Tree, KNN, and MLP, for classifying crops with Random Forest classifying with 95% highest accuracy and 0.92 kappa score showing the high promise of high spatial resolution satellite images and ML models in agricultural observation [19].

The review emphasizes the use of a variety of remote sensing (RS) techniques, such as velocity, satellite imaging, aerial photography, and sensor-based data gathering, for agricultural monitoring. Microwave, thermal infrared (TIR), and visible radiation are directly used to assess soil moisture;. LiDAR is used for biomass estimation and provides high spatial resolution. The main products obtained from these techniques are biomass/yield estimation, soil moisture content, and monitoring for drought [20]. The study employed Sentinel-2 satellite data for near real-time crop health monitoring, utilizing vegetation indices such as the Vegetation Condition Index (VCI) and Normalized Difference Vegetation Index (NDVI) to produce time series of crop health. The results contained correct maps of crop type containing an overall accuracy of 79.26% (Kappa value 0.737) as well as detailed crop phenology information—onset, greening, maturity, senescence—for Teff, wheat, onion, and sorghum [21].

3. Problem Statement

Crop health evaluation must be conducted precisely and timely in order to improve agricultural output and food security. Traditional means of crop health monitoring are time- and labor-intensive and often have a limited spatial scope. A scalable and effective solution is offered by remote sensing technology, which uses images from satellites to enable ongoing, extensive vegetation condition monitoring. Effectively analyzing remotely sensed data is still difficult since crop varieties, environmental factors, and noise sources like cloud cover all vary. For precise crop health measurement, robust analysis methods that can access multi-temporal and multi-spectral satellite data are required. The accuracy and integrity of crop health assessments can be significantly improved by combining remote sensing with advanced analytical tools like vegetation indices and machine learning. This allows precision farmers to make well-informed decisions.

4. Motivation

Remote sensing and GIS are two prominent instances of geospatial technology that provides several powerful tools for determining agricultural conditions over large areas at precise spatial and temporal resolutions. Through the processing of satellite photos (like Sentinel-2), crop indices (like NDVI, EVI, and NDRE), and machine learning algorithms, scientists and farmers can detect early warning signs of disease infection, crop stress, and nutritional deficits. Multi-temporal study of crop growth patterns, the development of crop health maps, the verification of ground truth data, and the implementation of precision agriculture decision-support systems are the areas of application for this work. In addition to improving monitoring effectiveness, it makes prompt

intervention possible, which leads to increased output, reduced input costs, and sustainable agriculture.

5. Objectives

1) To study Remote Sensing and GIS for Crop Identification & Analysis.
2) To collect data from different sources.
3) To design and development of database.
4) To develop and implementation of Techniques for Crop Identification & Analysis for precision agriculture.
5) To develop effective model for crop analysis.

6. Study Area

The geographical region chosen for this research is Sillod, as indicated in figure 1, which is located at 20.3079° N and 75.6528° E in the Chhatrapati Sambhaji Nagar district of Maharashtra, India. At the average elevation of 620m above the sea level Sillod is located. This region has somewhat tropical arid climate with different climate situations like mild winter, hot summer and moderate rain. Agriculture is the region's economic backbone, employing the vast majority of its population. Cotton, soybean, sugarcane, wheat, and maize are the main crops grown in Sillod, with cotton and soybean being the most important Kharif crops. The rich black cotton soil (regur) with its great mineral and moisture-holding ability promotes intensive cultivation. This area was chosen based on its agro-ecological significance, presence of ground truth data, and availability of satellite imagery for remote sensing research. Sillod also offers a typical landscape for precision agriculture study, especially in terms of crop health monitoring, yield estimation, and adoption of machine learning and remote sensing methods.

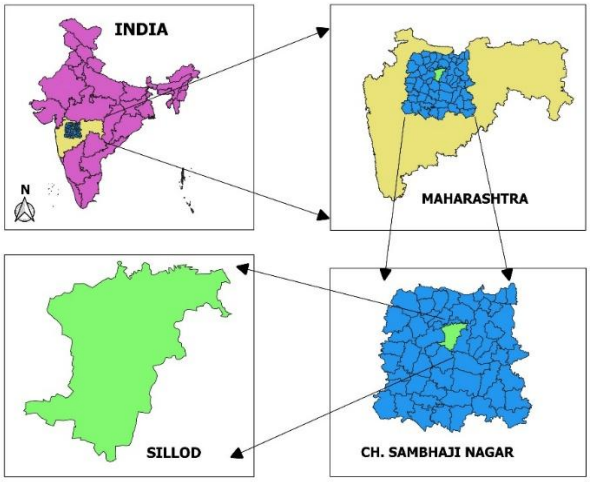

Figure 1: Study Area

7. Tools Used for Research Work

For our study on crop identification and health analysis, we used a mix of potent geospatial, statistical, and machine learning tools to guarantee precise data processing, visualization, and analysis. Acquisition and analysis of satellite pictures, creation of vegetation indexes, integration of ground truth data, and use of sophisticated modeling approaches defined the workflow Key tools employed in this research include Google Colab for running statistical analysis and machine learning-based prediction of crop health indicators, Google Earth Engine for satellite data processing and vegetation index production, and QGIS for spatial visualization and map creation. Accomplishing a strong, end-to-end research framework depended critically on each of these instruments.

7.1 Google Earth Engine (GEE)

For obtaining and processing satellite data and calculating vegetation indices with Sentinel-2A imagery. Google Earth Engine (GEE) is a cloud-computing platform for geospatial processing that is suitable for planetary-scale environmental data processing. It grants users access to multi-petabyte archives of satellite images and geospatial data and the computing power to perform analysis and manipulations of large data sets on Google's own computing machinery as shown in following figure 2. GEE in our study was integral throughout the data collection as well as the calculation of vegetation indices.

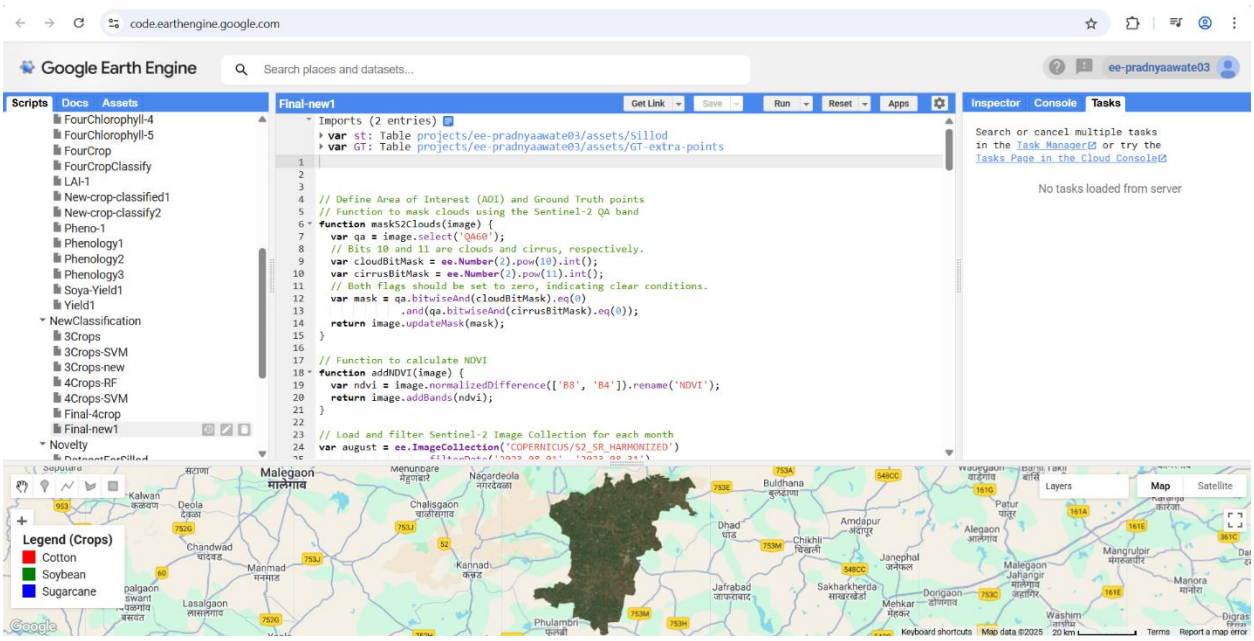

Figure 2: Google Earth Engine Platform for Geospatial Processing

Data Access:
We obtained Sentinel-2A imagery through GEE, which is a high-resolution multispectral satellite collection provided by ESA, which contains 13 spectral bands that can be leveraged for vegetation analysis. Its temporal resolution, i.e. 5 days revisit time, and its spatial resolution, i.e. 10m-60m, was therefore ideal for monitoring crop health over time.

Preprocessing:
Cloud masking based on QA60 band as well as image subsetting based on time of capture, cloud percentage, and geographical area of interest (AOI) were done easily in GEE.

Custom Vegetation Indices:
JavaScript coding allowed for the use of traditional vegetation indices, such as NDVI, EVI, and SAVI as well as user-defined indices, such as CSI, MCI, and RECI in GEE . These indices were exported as statistics or raster files and were computed at the pixel level.

Exporting Results:

Indexes could be exported from the platform in .CSV or .GeoTIFF files for additional statistical analyses or mapping.

Benefits:
The use of GEE greatly minimized processing times, avoided the necessity of locally downloading heavy satellite data, and provided a reproducible, scalable, and scriptable environment for monitoring vegetation over time.

7.2 QGIS

QGIS is Used for creating detailed maps, visualization of classified layers, spatial analysis, and integrating field data. QGIS is a free and open-source application designed for viewing, editing and analyzing geospatial data in a variety of formats and is a Geographic Information System (GIS) application. It has a robust cartographic visualization and spatial data manipulation capabilities with a user-friendly interface and is also well documented in regards to developing plugins. The main uses of QGIS in our work were:

Map Creation:
QGIS was used to create final thematic maps of land use points, ground truth samples, and vegetation indices. Each map was designed to include north arrows, coordinates and scale bars as well as legends when they would be useful for publication.

Shapefile Handling:

To ensure proper alignment with the Sentinel imagery used in GEE and Colab, a shapefile of the Area of Interest (AOI) was imported into QGIS and visualized.

Layer Integration:
We complemented satellite layers (NDVI, MCI, RECI, etc.) with ground truth data obtained by positioning at known latitude-longitude points to collect chlorophyll information in order to correlate and validate better in space .

CRS Management:
It was ensured that Coordinate Reference System were set correctly and consistently with Sentinel-2 and ground data, such as EPSG:4326 which correspond to WGS84.

Data Quality Control:
Outliers or misplaced coordinates were detected by visually exploring field data points in space prior to their input into statistical models.

Benefits:
QGIS was specifically used for the spatial visualization and to create the visuals and spatial layers necessary for analysis, reporting and publishing.

7.3 Google Colab

Google Colab is used to analyze crop indices and ground truth data statistically and using machine learning. A cloud-based Python development environment, Google Colab (Collaboratory) lets users write and run Python code via the browser, with no configuration necessary and free access to computational resources including GPUs and TPUs. Advanced statistical and machine learning-based analysis of vegetation indices obtained from GEE and ground chlorophyll measurements was done in our study using Google Colab: Using pandas, Colab was loaded with. CSV files exported from GEE that included custom vegetation indexes and chlorophyll values.

Exploratory Data Analysis (EDA): Using matplotlib and seaborn, visualizations including histograms, scatter plots, and correlation heatmaps were produced to grasp links between indexes and crop health. Using spectral indices as inputs, we predicted ground chlorophyll levels with several regression and deep learning models including SVR, Random Forest, ANN, CNN, and cGAN. Each model's performance was assessed using common measures including RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and R^2 Score, allowing us to pinpoint the most appropriate model. Visualization: Model predictions and residuals were shown to confirm performance trends and spot overfitting or underfitting. Advantages of Google Colab are, Shared code notebooks across team members were

effortlessly created. Google Drive integration greatly simplifies data storage, loading, and access. Hardware acceleration let us run complex deep learning models successfully using GPUs.

7.4 SNAP (Sentinel Application Platform)

SNAP is used for preprocessing Sentinel-2A imagery, which includes atmospheric correction, resampling, and subsetting. Purpose in research

Designed by the European Space Agency (ESA) especially for the analysis and preprocessing of data from Sentinel missions, SNAP (Sentinel Application Platform) is an open-source program. It is meant for optical and radar data processing and offers plugin compatibility for several sensors. SNAP was mostly employed in our studies for preprocessing raw Sentinel-2A Level-1C pictures before importing it into other systems. Important activities consisted of:

Using the Sen2Cor plugin, Level-1C Top-of-Atmosphere (TOA) reflectance data were converted to Level-2A Bottom-of-Atmosphere (BOA) reflectance, which is more suitable for vegetation analysis. To guarantee index calculation consistency, all bands were resampled to a shared spatial resolution of 10 meters.

Subsetting: The photos were truncated to our AOI, therefore lowering data volume and concentrating research. SNAP's tools were employed to visually check and assess the bands' integrity, metadata, and quality layers.

Using SNAP guaranteed the creation of correct, atmospherically corrected inputs, so boosting the dependability of plant indices and downstream machine learning outcomes.

8. Methodology

Our entire research methodology starts with data gathering, where Sentinel-2A satellite imagery is obtained together with related ground truth data gathered from the field. During preprocessing, necessary tasks like layer stacking, region clipping, cloud masking, and resampling were executed in order to condition the imagery for analysis. Subsequently, different vegetation indices were calculated, such as simple ratio-based indices, soil-adjusted and atmospherically resistant indices, red edge-based indices, and chlorophyll/pigment-related indices, designed to improve certain crop health characteristics. These generated indices were then used as inputs to train machine learning classifiers such as Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors. Finally, accuracy measurements like Overall Accuracy, User Accuracy, Producer Accuracy, and Kappa coefficient were used to evaluate the performance of the categorization

models. Some of the most important experiments and analyses carried out as part of our research project to evaluate crop health and classification are shown in the ensuing subsections. The thorough technique utilizing Sentinel-2A imagery and field-gathered ground truth data serves as the foundation for these experiments.

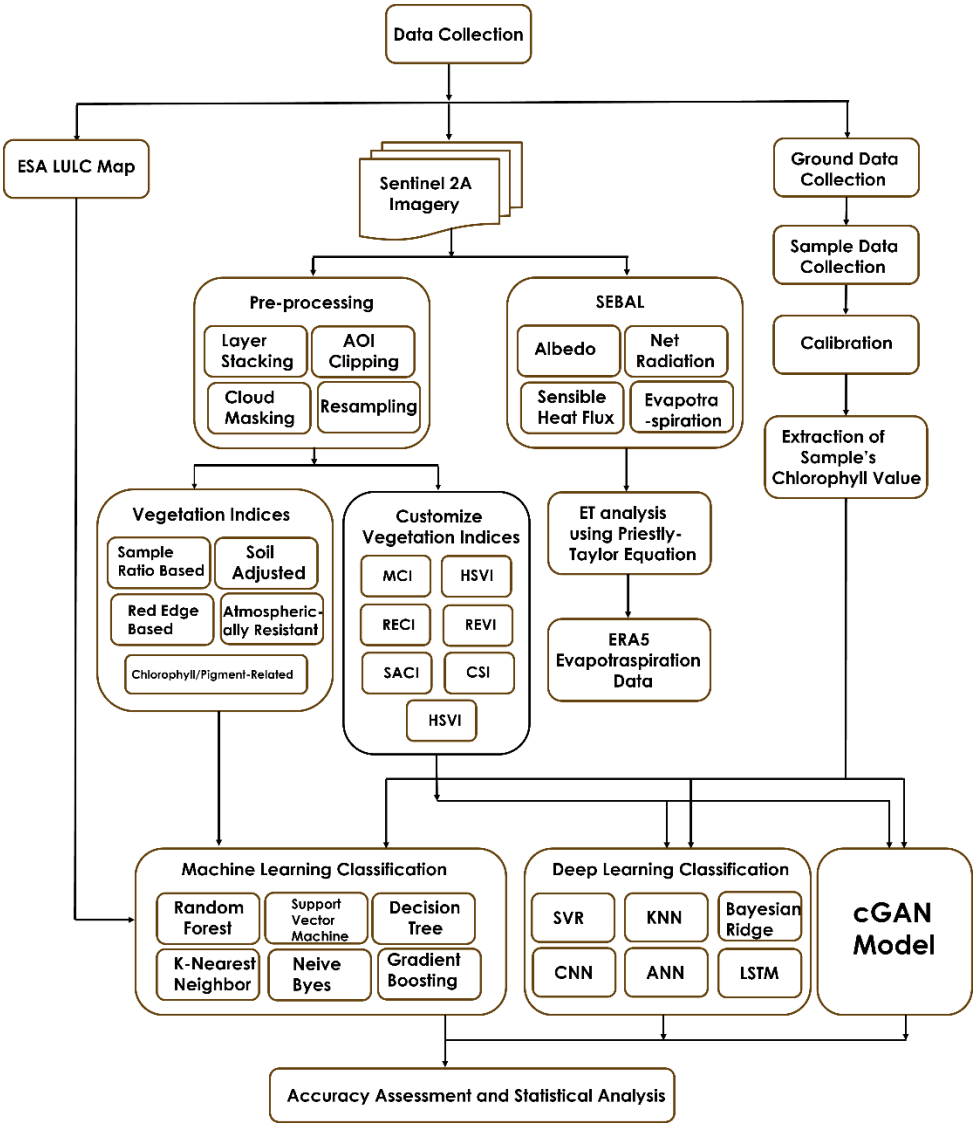

Figure 3: Proposed Methodology

8.1. Sentinel-2A Imagery

Sentinel-2A is commissioned under the Copernicus Programme of the European Space Agency and was successfully launched on June, 23 2015. It was intended for Earth observation and

provides high resolution multispectral data which has proven to be invaluable for the agricultural, forestry, and environmental monitoring communities .

Sensor System

Sentinel-2A carries the MultiSpectral Instrument (MSI), which can acquire images in 13 spectral bands in the visible (VIS), near infrared (NIR), and shortwave infrared (SWIR) parts of the electromagnetic spectrum. By also operating the second satellite, Sentinel-2B, it offers near-simultaneous global coverage at a maximum latitude of 56° South and 84° North, with a 5-day revisiting time.

Spatial Resolution

The multi-scale spatial resolution of Sentinel-2A allows it to be used for Earth observation applications at different levels. The MultiSpectral Instrument (MSI) on board records data at three spatial resolutions, which are 10 meters, 20 meters and 60 meters, according to the spectral band. The bands at 10-meter resolution, B2, B3, B4 and B8, contain information in the visible and near-infrared spectra that are particularly useful for extracting high-resolution information on vegetation and land cover classification. Bands B5, B6, B7, B8A, B11 and B12, all of which are found on the 20 meter set, covers the red-edge and shortwave infrared and can be used to monitor crop stress, chlorophyll levels, and soil moisture amongst others. The 60 meter bands B1, B9 and B10 are mainly used for atmospheric correction purposes like the detection of cirrus clouds and water vapor helping to provide more accurate land surface reflectance measurements.

Temporal and Radiometric Resolution

Sentinel-2A has a revisit time of 10 days and, when paired with its twin, Sentinel-2B, revisits every 5 days. Such frequent revisit time provides the ability to regularly capture information on the land surface in constant change, including vegetation phenology, crop cycles, and land cover changes. Plus, Sentinel-2A has a 12-bits radiometric capability, which allows it to capture 4096 levels of intensity per spectral band. It enables accurate identification, at a high level of detail, of minimal variations of reflectance at the surface level which is indispensable for applications as sensitive as chlorophyll estimation, early drought detection, and micromonitoring of vegetation health .

Applications

Sentinel-2A images have numerous applications in agriculture, the environment, forestry, hydrology, and urban planning, among other fields . In the agricultural field, imagery is applied in vegetation index calculations, NDVI, SAVI and EVI for example, for crop classification, yield estimation and mapping chlorophyll content. The red-edge and NIR bands improve the potential of detecting minor stress in crops and estimating biophysical parameters such as Leaf Area Index (LAI) or canopy water content . Applications of Sentinel-2A in the field of environmental studies include land degradation and wetland mapping, forest loss, water quality, and flooding extent mapping . SWIR bands have been useful in soil moisture and burned areas analysis, and minerals content. This free and open access to data makes Sentinel-2A fundamental for large scale multi-temporal studies using platforms such as Google Earth Engine.

Band	Central Wavelength (nm)	Bandwidth (nm)	Resolution (m)	Region of Spectrum	Primary Use
B1	443	20	60	Visible (Blue)	Aerosol scattering, atmospheric correction
B2	490	65	10	Visible (Blue)	Bathymetry, water body mapping, vegetation analysis
B3	560	35	10	Visible (Green)	Vegetation vigor, land classification
B4	665	30	10	Visible (Red)	Chlorophyll absorption, vegetation discrimination
B5	705	15	20	Red Edge	Vegetation monitoring, stress detection
B6	740	15	20	Red Edge	Chlorophyll content, crop condition analysis
B7	783	20	20	Red Edge	Biomass estimation, plant structure
B8	842	115	10	Near Infrared (NIR)	Vegetation monitoring, NDVI, biomass studies
B8A	865	20	20	Narrow NIR	LAI, canopy structure, crop health
B9	945	20	60	Water Vapor	Atmospheric correction, water vapor content
B10	1375	30	60	Cirrus Detection	Thin cirrus cloud screening
B11	1610	90	20	SWIR	Soil moisture, drought assessment, crop residue mapping
B12	2190	180	20	SWIR	Biomass burning, canopy water content, soil mineralogy

Table 1: Sentinel-2A Band Specifications

Electromagnetic Spectrum Context

Table 1 describes the band specification of sentinel-2A imagery. Capturing reflectance data across the visible (VIS), near-infrared (NIR), red-edge, and shortwave infrared (SWIR) sections of the electromagnetic spectrum—that is, from roughly 443 nm to 2190 nm—Sentinel-2A Helping in natural color imaging and vegetation identification, bands B2 (blue), B3 (green), and B4 (red) are present in the visible spectrum. Being very sensitive to chlorophyll concentration, the red-edge bands (B5, B6, B7) are uniquely located between the red and NIR bands, hence are crucial for plant stress detection. The NIR bands (B8, B8A) are used for evaluating plant vigor, canopy architecture, and biomass estimation. The SWIR bands (B11 and B12) allow the detection of water content in vegetation and soil, as well as the identification of burn scars and mineral properties. Although lower in spatial resolution, atmospheric bands such B1, B9, and B10 are used for correcting atmospheric effects and removing thin cirrus clouds from analysis. This spectral range offers a thorough set of data for multi-dimensional land surface characterization.

8.2. Image Pre-processing

Ensuring that the input images are geometrically, radiometrically, and spectrally ready for next study, preprocessing is a crucial stage in satellite data processing. Layer stacking, AOI clipping, resampling, and cloud masking among other preprocessing techniques were used in this study to boost the usefulness and quality of Sentinel-2A multispectral images. These processes help to eliminate pointless areas, balance spatial resolutions, promote effective data integration, and lessen atmospheric noise.

Integration of several spectral bands from multispectral satellite imagery into one composite picture is known as layer stacking. Every band gathers reflectance information at a certain wavelength and carries unique biophysical data. Layer stacking in Sentinel-2A processing combines chosen bands—visible (B2, B3, B4), red-edge (B5–B7), NIR (B8, B8A), and SWIR (B11, B12)—into a consolidated multiband raster dataset. This stage helps machine learning models' calculation of vegetation indexes and input preparation by guaranteeing spectral coherence over bands. Usually layer stacking is carried out utilizing image processing tools like SNAP, QGIS, or Python-based libraries like GDAL and rasterio.

Clipping is the spatial subsetting of imagery to a specified Area of Interest (AOI), therefore limiting the examination to a particular geographic area pertinent to the aims of the investigation. This procedure coordinates satellite pictures with ground reference data, deletes superfluous data, and lowers computational load. Usually specified using a polygon shapefile or GeoJSON boundary, the AOI serves to mask or extract the appropriate section of the satellite image. Standard procedure in GIS systems like QGIS or automated using scripts in Google Earth Engine (GEE), AOI clipping uses the clip() function to spatially subset the collection.

Resampling is the technique whereby the spatial resolution of satellite bands is changed to ensure consistency across the dataset. Sentinel-2A offers images at several spatial resolutions (10 m, 20 m, 60 m) and is required for many analytical applications—such as vegetation index computation or machine learning model training—to resample all bands to a common spatial resolution (typically 10 m). Nearest neighbor, bilinear interpolation, and cubic convolution are among among common resampling methods; method choice depends on the trade-off between spectral integrity and computational efficiency. Resampling guarantees precise pixel-level calculations, avoids spatial mismatches, and aligns pixel grids across bands.

Crucial preprocessing approach to remove cloud-contaminated and cloud-shadowed pixels from satellite images to guarantee the accuracy of reflectance-based research, cloud masking guarantees reliability. Automatic cloud detection is enabled by a Scene Classification Layer (SCL) and cloud probability products (e. g. , QA60 band) included in Sentinel-2A imagery. Algorithms such as Sen2Cor in SNAP or 's2cloudless' in Google Earth Engine utilize spectral thresholds and machine learning to identify and mask cloudy pixels. Good cloud masking guarantees the robustness of classification and regression models employed in environmental analysis and agricultural monitoring, improves the temporal consistency of time series data, and avoids vegetation index calculation abnormalities.

8.3. Vegetation Indices

Derived from the reflectance values of multispectral satellite data, particularly in the Visible (VIS), Near-Infrared (NIR), and Red Edge (RE) regions of the electromagnetic spectrum, vegetation indexes (VIs) are dimensionless spectral markers. These indexes measure key vegetative features including chlorophyll content, leaf area index (LAI), biomass, plant vigor, and canopy structure, therefore helping to monitor crop health, identify stress, and project yields. Combining particular bands (e. g. , Red, NIR, Green, Red Edge), every index reacts differently to physiological and structural plant characteristics. Early stress symptoms may be identified, nutrient state evaluated, and crop development phases monitored over time using vegetation indices in crop health monitoring. Below table 2 describes different vegetation indices used for our study.

No.	Vegetation Index	Mathematical Formula	Purpose	Sensitivity to Crop Health
1	**NDVI** (Normalized Difference Vegetation Index)	(NIR - Red) / (NIR + Red)	General vegetation greenness and vigor	Highly sensitive to chlorophyll content and plant biomass
2	**CIG** (Chlorophyll Index - Green)	(NIR / Green) - 1	Chlorophyll concentration estimation	Effective for early stress detection in dense vegetation
3	**CIRE** (Chlorophyll Index - Red Edge)	(NIR / Red Edge) - 1	Sensitive to chlorophyll in high biomass canopies	Useful in nitrogen monitoring and plant pigment variations
4	**CVI** (Chlorophyll Vegetation Index)	(NIR × Red) / ($Green^2$)	Chlorophyll and pigment density	Enhances separation of chlorophyll content in crops
5	**DVI** (Difference Vegetation Index)	NIR - Red	Basic green biomass and canopy density	Linear relation to leaf biomass and leaf area index
6	**EVI** (Enhanced Vegetation Index)	2.5 × (NIR - Red) / (NIR + 6×Red - 7.5×Blue + 1)	Improved NDVI under high biomass and atmospheric conditions	Better performance in dense canopy and soil backgrounds
7	**GEMI** (Global Environmental Monitoring Index)	[2×(NIR^2 - Red^2) + 1.5×NIR + 0.5×Red] / (NIR + Red + 0.5)	Environmental and vegetation structure monitoring	Minimizes atmospheric and soil brightness effects
8	**GNDVI** (Green NDVI)	(NIR - Green) / (NIR + Green)	Photosynthetic activity and chlorophyll concentration	Highly responsive to nitrogen status and plant health
9	**IPVI** (Infrared Percentage Vegetation Index)	NIR / (NIR + Red)	Normalized green vegetation	Simple and sensitive to green vegetation amount
10	**IRECI** (Inverted Red-Edge Chlorophyll Index)	(RE3 - Red) / (RE1 / RE2)	Chlorophyll estimation using multiple red-edge bands	Useful in crop nitrogen status and stress detection
11	**MCARI** (Modified Chlorophyll Absorption Ratio Index)	[(RE - Red) - 0.2×(RE - Green)] × (RE / Red)	Chlorophyll content and canopy photosynthetic capacity	Strongly correlated with chlorophyll and LAI under various stresses
12	**NDRE** (Normalized Difference Red Edge Index)	(NIR - RE) / (NIR + RE)	Vegetation status and chlorophyll in early canopy stages	More effective than NDVI in dense crops and late stages
13	**PSRI** (Plant Senescence Reflectance Index)	(Red - Blue) / RE	Leaf senescence and pigment degradation	Indicates crop aging and stress from nutrient deficiency
14	**SAVI** (Soil-Adjusted Vegetation Index)	[(NIR - Red) / (NIR + Red + L)] × (1 + L), L=0.5	NDVI variant for soil brightness correction	Effective in low vegetation cover and early growth stages
15	**TNDVI** (Transformed NDVI)	√[(NDVI + 0.5)]	Enhancement of NDVI sensitivity	Increases differentiation in mid-range vegetation densities

Table 2: Vegetation Indices Table

8.4. Customize Vegetation Indices

To improve the precision of crop health monitoring beyond conventional vegetation indices, we created a set of seven new vegetation indices especially fit for agricultural uses using crop health–sensitive spectral bands—particularly from the red, red-edge, and near-infrared regions of Sentinel-2A images. These indices were created to capture minute physiological and structural differences in crop canopies, which conventional indices often miss. Leveraging red-edge reflectance features, the Modified Chlorophyll Index (MCI) and Red-Edge Chlorophyll Index (RECI) were devised to provide better sensitivity to chlorophyll level. Under sparse or heterogeneous crop cover, the Red Edge Vegetation Index (REVI) and Soil-Adjusted Chlorophyll Index (SACI) combine soil reflectance correction and red-edge position to improve performance. For stress detection, the Canopy Stress Index (CSI) and Hybrid Stress Vegetation Index (HSVI) combine information from many spectral areas linked to water content and pigment degradation to detect early biotic and abiotic stress. Together, these indices provide a strong foundation for accurate and prompt assessment of crop health in precision agriculture.

8.5. Classification

Using multispectral remote sensing data and generated vegetation indices, we used a variety of machine learning (ML) classifiers in our investigation to examine and categorize crop health and types. Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Gradient Tree Boosting (GTB), Naive Bayes (NB), and K-Nearest Neighbor (KNN) comprise the ML models utilized. These models were selected for their robustness, interpretability, and ability to manage high-dimensional data. While SVM is useful in handling non-linear data spaces via kernel functions, particularly Random Forest and Gradient boosting are ensemble-based approaches noted for reducing overfitting and increasing categorization accuracy. Intuitive rule-based learning is provided by decision trees; naive Bayes offers probabilistic modeling based on feature independence; and KNN allows simple classification based on spectral similarity, which is quite pertinent for investigations on vegetation.

Besides traditional machine learning models, we included several deep learning (DL) approaches to capture the sophisticated, non-linear interactions found in temporal and spectral data. Because of their ability to automatically retrieve spatial and spectral features, models such the Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) were used for pixel-based and image-based classification applications. For dealing with time-series vegetation index data, the Long Short-Term Memory (LSTM) network was introduced so as to model temporal crop dynamics and health advancement. Furthermore, KNN (employed in both ML and DL approaches), Bayesian Ridge Regression and Support Vector Regression (SVR), were incorporated for continuous variable prediction, including estimating chlorophyll content or crop yield. By combining ML and DL techniques, this hybrid framework improved model generalization and

performance in a range of agro-ecological situations, therefore enabling thorough and accurate assessment of crop health.

8.6. cGAN Model

A deep learning model known as a generative adversarial network (GAN) consists of two neural networks—a generator and a discriminator—trained simultaneously in a competitive manner to produce realistic synthetic data. GANs are helpful for data quality improvement, synthetic vegetation index pattern creation, and increased model stability in crop health analysis, especially when dealing with small or imbalanced datasets. Using ground chlorophyll values as conditioning labels and customized vegetation indices as input characteristics, we implemented a conditional GAN (cGAN) in our study to properly model and predict crop health patterns based on spectral responses.

8.7. Accuracy Assessment and Statistical Analysis

To assess the performance of both classification and regression models employed for crop health analysis in our study, a thorough accuracy assessment was carried out. We computed Producer's Accuracy, User's Accuracy, Total Accuracy, and the Kappa Coefficient for classification jobs. Accounting for class-specific accuracy as well as agreement beyond chance, these indicators helped evaluate the model's ability in accurately recognizing crop kinds or health situations. To keep track of model generalization and identify overfitting or underfitting throughout deep learning and machine learning systems, we also assessed training, validation, and testing accuracies.

For regression-based studies, especially when estimating continuous variables such crop yield or chlorophyll concentration, we used statistical assessment measures including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). Descriptive statistical tools like mean, median, and standard deviation were employed as well to help one grasp the distribution and variation of expected versus observed data. Especially helpful for validating the output of our conditional GAN model for crop health assessment, in one case we used the Bland-Altman plot, a strong technique for evaluating agreement between predicted and ground truth values. This multi-metric evaluation strategy guaranteed a demanding and accurate validation of our presented approaches.

9. Implementation of Methodology

9.1 Land Use Land Cover

We have undertaken Land Use Land Cover (LULC) mapping for the Sillod area through the implementation of machine learning models—Random Forest (RF) and K-Nearest Neighbor (KNN). It commenced with Sentinel-2A imagery layer stacking and generation of False Color

Composite (FCC) for the visible delineation of predominant land cover classes like water, built-up areas, barre land, and vegetation. Following the detection of these distinctive characteristics, imagery was clipped to the Area of Interest (AOI) in order to narrow the focus for analysis. Both RF and KNN algorithms were used subsequently for classification. High classification performance was detected, with a total accuracy of 96.6779% for Random Forest and 98.6425% for K-Nearest Neighbour.

9.2 Vegetation Cover Assessment

This study uses Sentinel-2A multispectral imagery to provide a thorough analysis of the vegetation cover in the Sillod area of the Chhatrapati Sambhaji Nagar district, Maharashtra. In order to distinguish between different vegetation types, such as sparse, moderate, and dense vegetation, our research focuses on the computation of well-known vegetation indices, such as NDVI, SAVI, and GNDVI. By using a semiautomatic object-based classification method, we were able to identify features with excellent results. The accuracy assessment of the study yielded encouraging results. The NDVI demonstrated a remarkable 90.69% overall accuracy, with SAVI and GNDVI following closely behind at 83.58% and 93.23%, respectively. These results highlight the NDVI and GNDVI's potential usefulness for extracting vegetation in our study area. It illustrates how important it is to use Sentinel-2A imagery and sophisticated spectral indices for accurate vegetation analysis in Sillod, Maharashtra's changing landscape.

9.3 Crop Classification

We started by classifying three crops: cotton, soybeans, and sugarcane. In order to evaluate model performance across a variety of crop types, the analysis was then expanded to four crops: cotton, maize, wheat, and sugarcane. A new methodology was used.

9.3.1 Machine Learning-Driven Temporal Analysis for Crop Classification Using Sentinel-2A for Cotton, Soybean, and Sugarcane

The present study classified three main crops, that are, cotton, soybean, and sugarcane, on Sentinel-2A multispectral temporal data. Necessary processing in regard to cloud masking, NDVI calculation, and image clipping were conducted to assure data quality followed with layer stacking. Crop classification was performed using machine learning classifiers such as Random Forest (RF) and Support Vector Machine (SVM). In the RF classifier, overall accuracy is 94.44%, producer's accuracy is 92.31%, the user's accuracy is 80%, and the Kappa Coefficient is 0.8776. The SVM classifier performed noticeably inferior than the RF classifier, with an overall accuracy of 88.89%, a producer accuracy of 84.62%, a user accuracy of 99%, and a Kappa coefficient of 0.7778. Though SVM was highly accurate, with a UA of 99%, it

turned out less significant results in overall and producer's accuracy as compared to RF. Besides, RF performed much better when generalized to validation accuracy of 97.91% compared to that of SVM, which was 95.83%. These results indicate that RF can be an efficient and reliable approach for crop classification. The significance of our work lies in establishing the Random Forest classifier's applicability and superiority for accurate crop classification, which is required for effective agricultural planning and management in precision agriculture.

9.3.2 Crop Discrimination and Classification Using Sentinel-2A and Machine Learning Techniques

This study examines the ability of Support Vector Machine and Random Forest classifiers to distinguish cotton, wheat, maize, and sugarcane using Sentinel-2 imagery. Both classifiers were trained and tested using ground truth data, with accuracy determined by the User's Accuracy, Producer's Accuracy, Overall Accuracy, and Kappa coefficient. The outcome revealed RF as having a better OA (83.33%) and Kappa value (0.77) than SVM (66.66% OA, 0.55 Kappa), reflecting a better classification performance. RF also had a better validation accuracy (97.91%) than SVM (95.83%). Although both models performed well in classifying crops, moderate UA values reveal room for improvement. The research emphasizes the efficacy of RF for crop categorization and recommends future enhancement with the use of sophisticated machine learning methods and multi-temporal data fusion for more efficient agricultural surveillance.

9.4 Crop Yield Prediction

The research explores a machine learning-based approach to soybean yield prediction using time-series Sentinel-2A imagery for Sillod, Maharashtra, with specific emphasis on Nillod village as the Area of Interest (AOI). NDVI and EVI values were extracted from Sentinel-2A's multi-spectral bands that cover key vegetation indicators to monitor crop health during the growing season. The AOI was clipped to focus on the selected agricultural area, hence accurately representing conditions. Using a Random Forest model with part of the datasets on vegetation indices and available ground truth yield data that are to be used during model testing, this provides for an ensemble learning methodology wherein numerous decision trees culminate to give an effective yield prediction with robustness to individual noise factors. The validation results returned an RMSE of 202.07 kg/ha, which means that the model has good prediction accuracy. Yield Map As can be seen from the final yield map, the mean soybean yield across the AOI is 2875.39 kg/ha. In keeping with the scalability aspect for agri-yield estimation prediction, the results lend significant potential towards crop region tracking and resource conservational agriculture. Thus, timely prediction through integration of earth observatory-based satellite dataset exploitation using machine learning results provide

valuable input in pursuit of optimal agricultural practice production to help maintain the sustain scale.

9.5 Evapotranspiration Estimation

The objective of this study is to apply Sentinel-2 satellite data for the monitoring of evapotranspiration of various crop cycles in Sillod, Maharashtra, India, including cotton, sugarcane, wheat, and maize. It uses a combination of some ET estimation methods, such as simplified ET and Priestley-Taylor methods, with net radiation (Rn) and sensible heat flux (H) calculations to estimate water extraction for each crop at four different times in June 2023 to February 2024. Some trends noticed here are that Rn was pretty consistent and high with fluctuating H values depending on the crop type or the growth stage. The minimum ET map values with the simple approach showed low minimum values for all study periods suggesting extensive water loss to ET processes. Spatial ET map variabilities were noticed with the Priestley-Taylor method, where it exhibited red and yellow color palettes that consider different crop water demands. To verify Sentinel-2-derived ET estimates, benchmarking using ERA5 evapotranspiration was calculated. The average ERA5 evaporation value from vegetation transpiration amounts to $1.21 \times 10 - 10$ in units of m^2/s, which compares well with the mean obtained from NDVI on Sentinel-2 equaling 0.1636. This cross-validation test makes sure our estimates of ET by Sentinel-2 are compatible with global datasets, which further supports the reliability and accuracy of the results derived. This study demonstrated strong effectiveness of a technique combining satellite-based ET estimation with remote sensing for the support of precision agriculture and sustainable water management. The findings are well-suited to provide valuable insights into optimizing crop water use in semi-arid regions, focusing on the potential of remote sensing for improving agricultural monitoring and resource planning.

9.6 Crop Chlorophyll Content Mapping

We assessed crop chlorophyll content in our research with two distinct methodologies. The first approach was directed towards mapping chlorophyll content for cotton crops alone based on vegetation indices of Sentinel-2A images. The second approach generalized the assessment to a number of crops such as cotton, maize, wheat, and sugarcane that have different spectral responses and growth patterns. Although both methods attempted to quantify chlorophyll content, they utilized different methods that were specifically suited to the type of crop and the

character of ground truth data, underlining the flexibility and scalability of our framework of analysis.

9.6.1 Mapping Chlorophyll Content in Cotton Crop

This study uses Sentinel-2 imagery and on-field measurements to map chlorophyll content in cotton fields, with the goal of improving precision agriculture using advanced remote sensing techniques. Sentinel-2A imagery was pre-processed by clipping and resampling to concentrate on the Sillod region, and three vegetation indices (VIs)—Triangular Normalised Difference Vegetation Index (TNDVI), Chlorophyll Index-Red Edge (CI-RE), and Normalised Difference Red Edge (NDRE)—were used to estimate chlorophyll levels. The data was statistically analysed by computing the mean, median, standard deviation, correlation coefficients, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) for both the on-field chlorophyll measurements and the VIs. The results showed moderate to strong negative correlations between the indices and on-field values, with correlation coefficients of -0.5579, -0.6437, and -0.6253. The Bland-Altman analysis was used to evaluate the agreement between the indices and on-field measurements, and it revealed that NDRE produced the most consistent estimates with the narrowest ranges of agreement to the mean difference. Scatter plots of the indices revealed unique patterns of clustering and outliers, with TNDVI and CI-RE exhibiting significant variability and NDRE demonstrating the best reliability. The data indicate that, while all three indices are effective for chlorophyll mapping, the NDRE provides the best trustworthy estimations. This study illustrates the potential for merging Sentinel-2 imaging with ground truth data to improve crop health monitoring and increase precision agriculture. The study emphasizes the significance of accurate calibration and validation of remote sensing techniques in order to make exact agricultural assessments.

9.6.2 Mapping Chlorophyll Content in Cotton, Maize, Wheat and Sugarcane Crop

This research compares the performance of vegetation indices (VIs) that have been extracted from Sentinel-2 images in measuring chlorophyll content through combining remote sensing information with ground truth values. Various VIs, viz. NDVI, EVI, GNDVI, CI_red, GCI, and TCARI, were examined based on statistical measures like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) in order to compare their predictive ability. Results showed that values such as GCI, CI_red, and EVI expressed relatively low errors, indicating their appropriateness for chlorophyll estimation. In addition, a Random Forest (RF) machine learning algorithm was used to improve prediction accuracy. The model gained an RMSE of 0.040754 and MAE of 0.032045, indicating the viability of machine learning in improving chlorophyll estimation. Yet, the R^2 value of -0.14746 and Pearson Correlation Coefficient of 0.098576 suggest room for improvement. Graphical representations such as scatter plots, residual plots, histograms, and comparative analysis gave further insight into the VIs vs. ground-measured chlorophyll values relationship.

This study highlights the potential of remote sensing and machine learning for precision agriculture and presents a scalable method for monitoring crop health. Future research could investigate the application of more spectral bands, multi-temporal feature analysis, and deep learning-based methods to more accurately predict with wider applicability.

9.6.3 Mapping Chlorophyll Content in Cotton, Maize, Wheat and Sugarcane Crop using Deep Learning Classifiers

For estimating the chlorophyll content of cotton, maize, wheat, and sugarcane, we tested and compared some deep learning models such as Deep Neural Network (DNN), 1D Convolutional Neural Network (1D CNN), Long Short-Term Memory (LSTM), and a combined CNN+LSTM model. The models were trained on vegetation indices we developed from Sentinel-2 spectral bands along with ground-truth chlorophyll measurements. Out of the models tried, the DNN provided an RMSE of 0.0535, MAE of 0.0421, and an R^2 of -1.41, which reflects a comparatively higher prediction error and lesser correlation with true values, possibly because it has limited temporal feature extraction ability. The 1D CNN model performed better with an RMSE of 0.0484 and MAE of 0.0391 but still had a negative R^2 of -0.97, indicating underfitting or inability to capture temporal dependencies.

There was considerable improvement with the LSTM, which is capable of working with sequential data. It reached an RMSE of 0.0408, MAE of 0.0309, and an improved R^2 of -0.41, showing the capability of modeling crop chlorophyll content temporal dynamics. The hybrid CNN+LSTM model performs best, combining spatial feature extraction by CNN with temporal sequence modeling by LSTM. This model had an RMSE of 0.0367, MAE of 0.0297, and R^2 of -0.13, showing the smallest prediction error and nearest approximation to actual chlorophyll values among all models tested. These results show that the use of both spatial and temporal features greatly increases the accuracy of chlorophyll prediction, with the CNN+LSTM architecture being best suited for accurate crop health monitoring in this research.

9.7 Novel cGAN Model for Crop Health Analysis

Using a Conditional Generative Adversarial Network (cGAN) trained on custom vegetation indices (VIs) extracted from Sentinel-2 imagery, we offer a fresh approach to crop health estimation in this study. Learned to forecast the chlorophyll content of crops—a crucial indication of plant vitality—the model is conditioned on seven precisely created VIs that capture various features of vegetation health. The performance of the suggested GAN model was measured against those of conventional regression models like SVR, Random Forest, and MLP. RMSE, MAE, and R2 were among the evaluation parameters used.

10.Conclusion

Experimental findings of our research validate the potential of merging Sentinel-2A satellite data with machine learning algorithms in the analysis of different dimensions of agricultural monitoring for the Sillod area. Land Use Land Cover (LULC) analysis was conducted for the Sillod area using Random Forest and K-Nearest Neighbour models. Important land cover elements such as water bodies, built-up, barren, and vegetation were detected using FCC images. Following clipping to the Area of Interest, both algorithms were run and produced high classification accuracies of 96.6779% for Random Forest and 98.6425% for KNN. This updated LULC mapping offers useful information on land use dynamics in the area and contributes to wider agro-environmental planning. By crop categorization, we were able to differentiate between large crop categories—initially among cotton, soybean, and sugarcane, and then to maize and wheat—demonstrating high accuracy using classifiers like Random Forest, SVM, and KNN. Crop yield estimation of soybean, with ground truth data support, confirmed the applicability of remote sensing and regression models for yield outcome prediction. The application of SEBAL model-based evapotranspiration estimates and NDVI gave valuable insights into water use patterns, aiding the detection of stress zones and making irrigation planning more efficient. Chlorophyll content mapping, carried out through two different methods, successfully captured variation in crop health, both in a targeted cotton study as well as in a wider multi-crop analysis involving cotton, maize, wheat, and sugarcane. Finally, Land Use Land Cover (LULC) classification of the Sillod area successfully mapped broad land classes like water bodies, built-up land, barren land, and vegetation, with Random Forest and KNN models both producing overall accuracies of over 96%. Together, these experiments demonstrate the potential of satellite-led, data-driven techniques in enabling precision agriculture, resource management, and sustainable land-use planning. This study introduces an integrated framework for crop health analysis using high-end remote sensing methods, bespoke vegetation indices, and deep learning, machine learning models. Establishing a region-specific spectral library for the region of Sillod and applying a conditional GAN and hybrid deep learning models enormously boosted the precision of chlorophyll estimation and crop health monitoring. The suggested methodology shows its capability for scalable data-driven farm analysis, bringing valuable inputs for precision farming and sustainable crop management.

11.Contribution Made to the Existing Knowledge

1) Multi-Source Data Fusion with Ground Validation for application of Machine Learning and Deep Learning Models
2) ESA's LULC-Guided Crop Classification

3) Temporal Composite-Based Crop Classification
4) Chlorophyll Estimation with ML-Backed Ground Calibration
5) ET Integration with Crop Health Monitoring
6) Yield Prediction and Validation using Satellite Features
7) Comprehensive Accuracy Assessment using Machine Learning Models.
8) Development of Novel Vegetation Indices
9) Creation of Spectral Library for the Sillod Region
10) Integration of Conditional GAN for Crop Health Modeling

12. Organization of Thesis

Chapter 1: Introduction
This chapter provides an introduction to crop identification and analysis using remote Sensing and GIS technologies. It will explain the significance of crop monitoring and management, highlighting satellite imagery. The chapter will also introduce the concept of precision agriculture and the importance of using data-driven approaches in agricultural management.

Chapter 2: Literature Review
The goals and objectives of the literature review are presented in this chapter. This chapter will review relevant literature on various aspects of crop analysis such as Remote Sensing for Crop Monitoring, Machine Learning in Agriculture, crop health analysis, including vegetation indices like NDVI, EVI, and chlorophyll-specific indices.

Chapter 3: Methodology
This chapter will outline the research methodology in detail. It will describe the approach used for collecting and processing Sentinel-2 imagery, and extracting vegetation indices. The chapter will also explain the use of different techniques.

Chapter 4: Results and Discussion
In this chapter, the results of crop classification and crop analysis for satellite imagery.

Chapter 5: Conclusion
This chapter will summarize the key findings of the research, emphasizing the impact of using remote sensing for precision agriculture. It will also discuss the limitations of the study and suggest future research directions, including potential improvements in model accuracy, integration with other data sources and expansion to other crop types or regions.

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